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Improving EMG-Based Muscle Force Estimation by Using a High-Density EMG Grid and Principal Component Analysis

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***Abstract*—The accuracy of predictions of muscle force based on electromyography (EMG) is an important issue in biomechanics and kinesiology. Since human skeletal muscles show a high diversity and heterogeneity in their fiber architecture, it is difficult to properly align electrodes to the muscle fiber direction. Against this background, we analyzed the effect of different bipolar configuration directions on EMG-based force estimation. In addition, we investigated whether principal component analysis (PCA) can improve this estimation. High-density surface-EMG from the triceps brachii muscle and the extension force of the elbow were measured in 11 subjects. The root mean square difference (RMSD) between predicted and measured force was determined. We found the best bipolar configuration direction to cause a 13% lower RMSD relative to the worst direction. Optimal results were obtained with electrodes aligned with the expected main muscle fiber direction. We found that PCA reduced RMSD by about 40% compared to conventional bipolar electrodes and by about 12% compared to optimally aligned multiple bipolar electrodes. Thus, PCA contributes to the accuracy of EMG-based estimation of muscle force when using a high-density EMG grid.**

***Index Terms*—Force estimation, heterogeneous muscle fiber architecture, human, principal component analysis, redundancy, surface electromyography.**

I. Introduction

ACCURATE and reproducible prediction of muscle force from surface electromyography (EMG) is an important goal in biomechanics and kinesiology. Conventionally, EMG is collected using a single bipolar electrode pair placed on the skin above the muscle belly. There is a fundamental limitation to the accuracy of this method due to the nature of the EMG signal. EMG signals constitute a summation of the motor unit action potentials, occurring within the detection area of the electrode. Since each of the motor unit action potentials is biphasic or triphasic and since they are not strongly synchronized, constructive and destructive superimpositions occur, leading to variance in the EMG amplitude that does not represent variance of muscle activation. Theoretically this problem can be avoided by recording from each motor unit separately. Although this is practically unfeasible, it suggests that the use of multiple, spatially distributed EMG channels, collecting independent information from separate sources, will improve the estimation of muscle force. Some studies have indeed shown that EMG-based estimation of muscle force can be improved by using multiple bipolar electrodes pairs [1]–[3] and with a grid of densely spaced monopolar electrodes (i.e., high-density EMG grid) [4]. In the latter study, spatially filtered signals from bipolar electrode configurations constructed from the channels in a high-density grid predicted force substantially better than the original signals from monopolar electrodes. Spatial filtering is preferably done in the direction of the propagating action potential, hence in the fiber direction. De Luca classified the orientation of the detection surfaces with respect to the muscle fiber as an important factor for EMG amplitude estimation [5]. Also SENIAM described the bipolar arrangement as significant factor in the estimation of muscle force [6]. Modeling work done by Merletti and co-workers [7] predicted that misalignment of electrodes with respect to the muscle fiber direction reduces the EMG amplitude.

These general recommendations pose a problem, since the electrodes can not easily be aligned with the muscle fiber direction with certainty. Human skeletal muscles show a rich diversity in muscle fiber directions. In addition, heterogeneity of the muscle fiber architecture can be found in some (if not most) skeletal muscles. For example, a pennate muscle like the gastrocnemius muscle has multiple fiber directions [8]. Unfortunately, precise descriptions of muscle architecture are lacking for many muscles. Hence, when using EMG, alignment with the underlying muscle fibers cannot always be achieved. In addition, experimental in vivo studies done with real-time ultrasonography showed muscle fiber direction to change with joint angle [9] and even during isometric contractions with increasing force [10]. Consequently, assumptions on fiber direction will always have a limited validity in isometric contractions and especially in dynamic activities.

High-density EMG grids collect many monopolar EMG signals over a relatively small collection surface. The signals can be considered in different ways. Most obvious is a post-hoc construction of electrode configurations; e.g., bipolar configurations or higher order derivations like the Laplacian configuration

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[11]. However, the monopolar signals can also be considered as a multidimensional dataset that probably contains redundant information to some degree. As an unbiased statistical method, principal component analysis (PCA) can be used to detect this type of redundancy in multivariate data by means of mode reduction [12], [13]. Thus, it may offer possibilities for the analysis of data obtained with a high-density EMG grid.

The aim of this study is twofold. First, we analyze the effect of different bipolar configuration directions on the quality of EMG-based force estimation. Second, we describe a procedure for muscle force estimation using a high-density EMG grid based on PCA that we compare to other EMG procedures, i.e., monopolar, bipolar, and Laplacian electrode configurations.

II. Methods

A. Measurement

The experimental methods and procedures have been described in detail elsewhere [4]. Briefly, eleven healthy subjects (age 28.0 ± 4.1 years, weight 67.6 ± 9.4 kg, and body length 1.8 ± 0.1 m) participated in the experiment after signing an informed consent approved by the ethical committee of the Faculty of Human Movement Sciences in Amsterdam, where the experiment was performed. The subjects performed isometric right arm extensions. The contraction was a rectangular pattern, consisting of a two-state isotonic contraction, starting at rest, followed by a plateau of 5 s and back to rest again. These efforts were measured at three different elbow angles (60°, 90°, and 130°) and at 30%, 50%, and 80% of the maximum voluntary contraction (MVC). In order to realize controlled contractions, real-time feedback of the force output and a line indicating the target level of contraction (%MVC), was provided to the subjects.

EMG and force output were measured simultaneously and synchronized. The force transducer (FUTEK L2353, ADVANCED SENSOR TECHNOLOGY, Irvine, CA, USA) was attached orthogonal to the forearm at the level of the wrist and recorded the extension force at a sampling rate of 1000 samples/s. EMG was collected with an active high-density EMG grid (BIOSEMI, Amsterdam, NL). This two-dimensional EMG grid consisted of 13 × 10 electrodes, covering a collection surface of 6.0 × 4.5 cm with gold-plated electrode tips of 1.2-mm diameter and an interelectrode distance of 5 mm. The skin was shaved and cleaned with alcohol and with an abrasive gel. Subsequently, an electrode cream (Minograf, SIEMENS-ELEMA AB, Germany) was applied in order to reduce the skin-electrode impedance. The EMG grid was attached over the muscle belly of the triceps brachii at the mid upper arm level with the longer side parallel to the longitudinal arm direction. A reference electrode and an active common mode sensor were placed over the bony part of the elbow (olecranon) and an active driven right leg electrode [14] was attached at mid arm level of the ulna. EMG signals were collected monopolarly, filtered with a bandpass of bandwidth 0.16–500 Hz and sampled at 2048 samples/s using a 16-bit A/D converter.

B. Analysis

Data analysis consisted of the following steps: high-pass filtering (10 Hz), compensation for an estimated electromechanical delay (100 ms), construction of a specific EMG configuration or PCA, full wave rectification, averaging over the EMG channels to get one time signal, low-pass filtering (10 Hz) and normalization of both the EMG signal and the force signal to an estimated mean over the plateau region. The plateau region was established by analyzing the derivative and variance of the force signal. The quality of the EMG-based estimation of muscle force was expressed as the root mean square difference (RMSD) between the normalized force and the normalized EMG. We quantified the relation between force and EMG fluctuations through the correlation coefficient. For the plateau region prior to further calculations, the EMG signal was smoothed using a 1st order Savitzky-Golay polynomial filter [15] (window size: 601 samples). Notice that this filter preserves the primary shape of the signal (even rapid fluctuations) while eliminating noise.

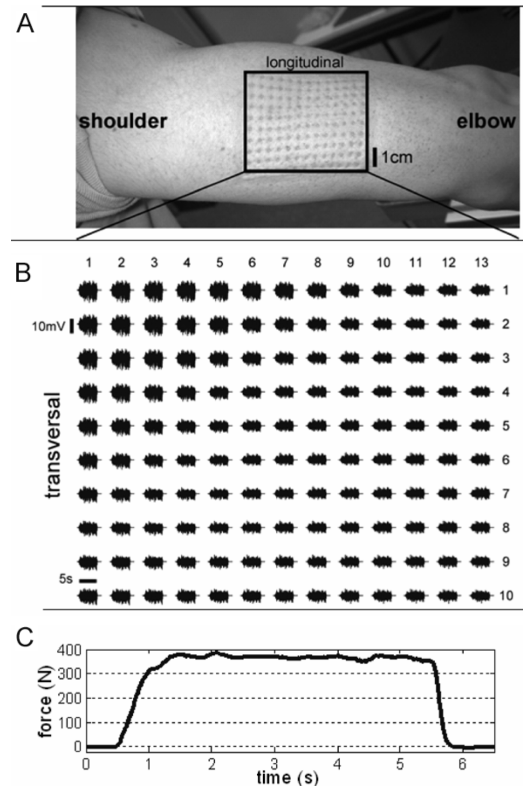

Fig. 1. (A) Skin-print of the high-density EMG grid over the muscle belly of triceps brachii, immediately after the experiment. (B) 130 monopolar EMG time signals subdivided in 13 longitudinal times 10 transversal electrodes, covering a surface of 6.0 × 4.5 cm, respectively. In this representative trial the subject had the arm in the most extended position (elbow angle of 130°) performing a static arm-extension of 80%MVC. (C) The rectangular pattern of the force being roughly isotonic during about 6 s at a force level of 80%MVC reaching around 370 N.

C. Electrode Configurations

The original monopolar signal set (MON), consisted of 130 monopolar signals collected by 13 × 10 electrodes [Fig. 1(B)]. From this set the following electrode configurations were constructed:

Multiple bipolar electrode configurations were constructed over the entire grid using closest neighboring electrode pairs in four different directions (see Fig. 2). These different configurations allowed to establish the optimally aligned multiple bipolar electrode direction (OMB) along the expected muscle fibers.

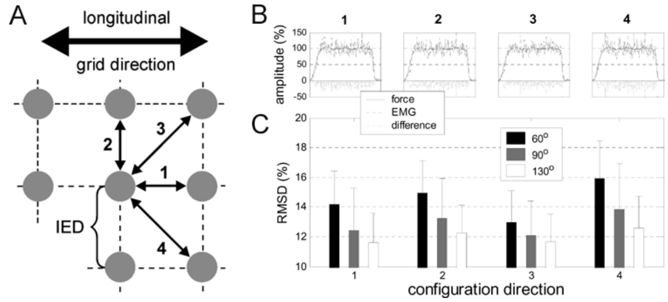

Fig. 2. (A) Section of the EMG grid, showing four different electrode pair directions (1–4), distributed with multiple bipolar electrodes over the entire grid. Dots represent electrodes (IED: interelectrode distance in the main directions) and arrows the direction of bipolar electrode configurations. The first direction is constructed with the difference of all neighboring electrodes aligned longitudinally. The following directions consist of the difference in the directions indicated by the numbered arrows (2–4). (B) One representative trial (130°-elbow angle, 50%MVC) showing normalized force and normalized EMG amplitudes for the 4 bipolar electrode directions. (C) RMSD for the 4 directions. Bars represent the average RMSD over subjects for different elbow angles; error bars represent their standard deviation. The Y-axis scaling was adapted to illustrate the effect of bipolar electrode directions.

A higher order spatial filtering, Laplacian-configuration (LAP), was constructed over the entire grid, having a central electrode weighted with a factor $+4$ and four closest neighboring electrodes weighted with a factor -1 (see Fig. 7, LAP) [11]. Furthermore, a conventional bipolar larger electrode configuration (CBI) having an interelectrode distance of 2.5 cm and electrode surfaces of approximately 1 cm^2 was simulated. These electrodes were placed along the longitudinal axis of the upper arm as recommended by SENIAM [6].

The latter CBI-configuration was constructed based the averages of the signals from five neighboring electrodes (see Fig. 7, CBI). This simulates a larger electrode since the metal to skin connection of each electrode, large or small, mainly consists of a so-called electric double layer with relatively high impedance compared to the underlying tissue impedances. This even applies to small intramuscular needle electrodes [16]. Therefore, the potential measured by an electrode equals the average of the potential distribution over the tissue directly below or around it. Within the spatial resolution of the electrode density of the grid, the average of the signals from five grid electrodes, therefore, realistically represents a larger electrode with an uninterrupted metal surface.

D. Principal Component Analysis

PCA in general transforms multivariate data into a set of linearly independent components, here referred to as principal modes [12] that contain so-called eigenvectors or principal axes onto which the original data are projected. To clarify this notation, recall that the calculation of modes is realized by diagonalization of the data's covariance matrix, to which eigenvectors and eigenvalues correspond. Importantly, the relevance of the modes can be ranked in terms of the eigenvalues that, for every mode, reflect its contribution to the data in terms of variance. For the present purpose, the eigenvectors describe the spatial distribution of the projected EMG over the grid that evolves in time according to the aforementioned projection. As will be shown below, we are not particularly interested in all individual modes but rather combine them into common parts and more independent parts. To this end, we split the ranked modes (ranked by descending eigenvalues order) into a sum of lower modes and a sum of higher modes. The first, i.e., a sum of mode 1 to a certain mode i, contains a large amount of variance and may be viewed as a common strong component, whereas the latter, i.e., a sum of mode i to mode 130, is in terms of variance less dominant, and focuses on residual differences between EMG channels.

E. Statistics

Statistical analysis was done in SPSS 11.5 (SPSS Inc., Chicago Ill, USA). Because of a small number of missing values, a univariate ANOVA with subject as a random factor rather than a repeated measures design was used. Three fixed factors were included: "electrode configuration," "elbow angle," and "contraction level" (%MVC). The dependent variable was the RMSD. The significance level was set at 5%.

III. Results

A. Raw Data

All 130 monopolar EMG signal amplitudes increased with an increase in force [Fig. 1(B)]. At the upper left corner of the grid, covering mainly the lateral head of triceps brachii muscle, EMG amplitudes appeared to be highest. For this representative trial (elbow angle: 130°; extension effort: 80%MVC), the subject performed an extension force of about 370 N.

B. Bipolar Configuration Direction

All EMG configuration directions nicely matched the entire contraction pattern of the force [Fig. 2(B)]. Over the plateau region differences in the signal-to-noise ratios (SNRs) can be seen, which affected the RMSD. The bipolar configuration direction had a significant main effect ($\mathrm{p} < 0.01$) on force estimation quality [Fig. 2(C)]. The lowest RMSD was found for the third electrode direction and was about $12.2 \pm 2.1\%$ (averaged over 3 elbow angles). Correspondingly, the highest RMSD was found for the orthogonal fourth electrode direction ($14.1 \pm 2.5\%$) with a 13% difference between directions 3 and 4. No main effect of contraction level was found ($\mathrm{p} = 0.9$), whereas elbow angle had a significant effect on the RMSD ($\mathrm{p} < 0.01$). Also the interaction between electrode direction and elbow angle was significant ($\mathrm{p} < 0.01$). The results indicate the lowest sensitivity to elbow angle for electrode direction 3 and the highest for direction 4.

C. Principal Component Analysis

From mode 1 to higher modes, the relative contribution (eigenvalue) decreased rapidly, as shown in Fig. 3. The contraction level did not have an effect on the eigenvalues ($\mathrm{p} = 0.5$), whereas elbow angle had a significant effect ($\mathrm{p} < 0.01$). The interaction effect between elbow angle and mode was also significant ($\mathrm{p} < 0.01$). For increasing elbow angles the eigenvalue of mode 1 showed a decreasing trend, whereas for the modes 2–6 an opposite trend could be seen. About $90 \pm 6\%$ of the measured monopolar EMG signals was represented by the first mode.

All three PCA outputs (projection, eigenvalue and eigenvector) are illustrated in Fig. 4. The peak-to-peak amplitude

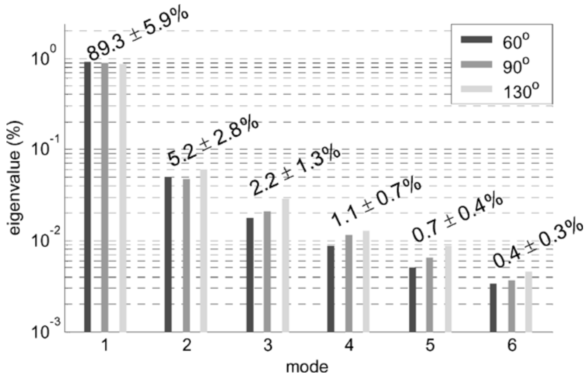

Fig. 3. Results of the PCA from the collected monopolar EMG datasets over all trials. Bars show mean eigenvalues for different elbow angles of the first 6 modes in descending order on a logarithmic scale. The numerical indication (%) indicates the mean eigenvalue per mode ± the mean standard deviation.

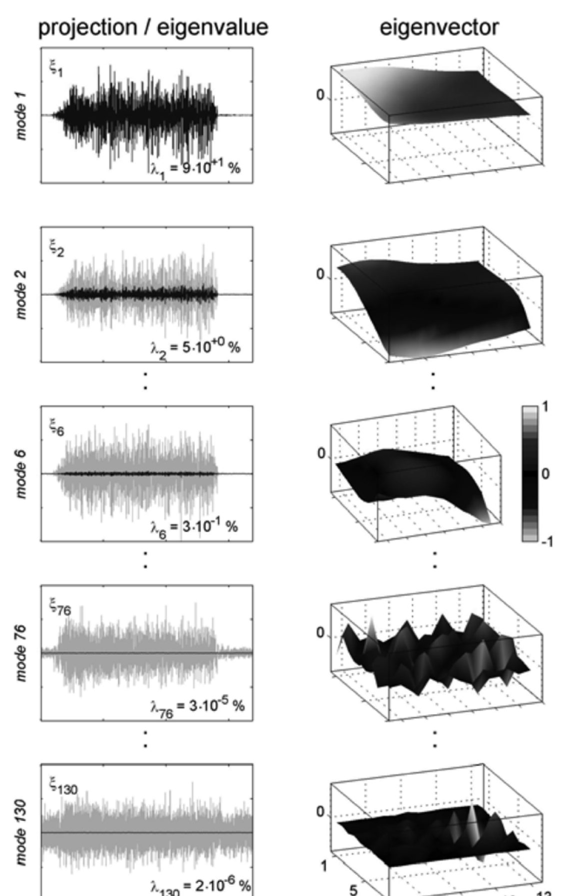

Fig. 4. Modes describing the output of the PCA on a monopolar EMG dataset of one representative trial (130°-elbow angle, 50%MVC). The left column shows the time evolution (projection ξ_i) and the relative contribution (eigenvalue λ_i). The right column shows the local distribution (eigenvector) over the 13 × 10 electrode grid. Both columns are arranged in descending eigenvalues order. Dark projections show normalized amplitudes and bright projections show additionally blown up amplitudes. The normalized eigenvector indicates high gained local distribution within the grid with bright colors and low gained local distribution with dark colors. Note the big change of projection-amplitude between ξ_1/ξ_2 and the changing EMG amplitude pattern for the last projection ξ_{130}. Note the change in distribution over the grid of the eigenvectors of higher modes, for instance from mode 76 on.

of the normalized projections showed a gradual decrease for increasing modes, with the biggest difference between the first two projections ξ_1 and ξ_2. The amplitude of very high modes, for instance mode 130, did not follow the force pattern anymore. The eigenvector of the first mode showed a fairly homogeneous local distribution over the EMG grid, having peak values at the upper left corner of the grid. The eigenvectors of mode 2 and mode 6 showed a less homogeneous local distribution, but with a still fairly smooth shape. Eigenvectors of higher modes (e.g., mode 76 and 130) appeared to have fluctuations within the local distribution.

D. The Optimal Sum of Higher Modes

To find the combination of modes that resulted in optimal force estimation, a sum of higher modes and a sum of lower modes was computed for the first 50 modes and compared to the force signal [Fig. 5(A)]. The sum of lower modes showed higher RMSD values than the sum of higher modes. For this typical example the curve of the sum of higher modes showed lowest RMSD for modes between mode 4 and mode 20, reaching a minimal RMSD of 9.4% using the sum of mode 6 to mode 130.

Between the sum of higher modes indicated by b and the sum of higher modes indicated by a and c a 43% decrease of RMSD was found. The three force and EMG patterns, as illustrated in Fig. 5(B), showed substantially stronger EMG amplitude fluctuations around the force for the first condition (a) than for the other two conditions (b, c). For the last condition (c) it can be seen that the EMG signal does not match the force pattern properly anymore, especially over the ascending and descending limb and over the zero-force level of the pattern.

To consider the fluctuations of the force and EMG, the correlations between both signals over the plateau region were calculated [Fig. 5(C)]. Over all conditions (subject, elbow angle and contraction level) median correlation coefficients for the sum of the higher modes from mode 1, mode 6 and mode 45 (points a, b and c in Fig. 5) were: 0.26 (range: −0.16:0.68), 0.52 (0.08:0.94) and 0.50 (−0.23:0.95), respectively. The sum of higher modes that yielded the minimal RMSD was computed for all trials and plotted in a histogram [Fig. 6(A)]. This distribution showed a relatively wide range with a median value at mode 8. Similarly, a histogram of the eigenvalues of the optimal sum of higher modes was computed [Fig. 6(B)]. This distribution was more peaked around a median eigenvalue of $1.5 \cdot 10 - 3$. Accordingly, this eigenvalue threshold was chosen for the following analysis to define the optimal sum of higher modes using PCA to predict muscle force.

E. EMG Procedures

Strongly significant differences in RMSD were found between the five different EMG procedures [$\mathrm{p} < 0.01$; Fig. 7(B)]. The CBI and MON resulted in the highest RMSD (17.9 ± 2.6% and 16.5 ± 2.7%, respectively). A lower RMSD was found for the PCA, OMB and LAP resulting in 10.8 ± 2.1%, 12.2 ± 2.1%, and 15.1 ± 5.1%, respectively. Median correlation coefficients over the entire rectangular pattern of the force and EMG signals were 0.97 (range: 0.93:0.99), 0.99 (0.97:1.0), 0.99 (0.97:1.0), 0.98 (0.95:0.99), and 0.98 (0.94:0.99) for the EMG procedures

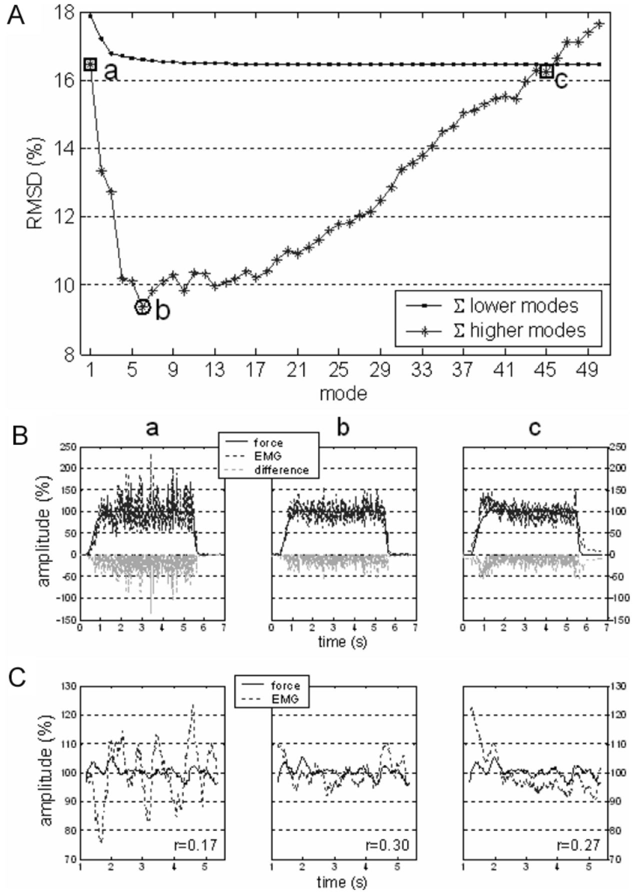

Fig. 5. (A) The RMSD for two different sums of modes from the PCA, for one representative trial (130°-elbow angle, 80%MVC). The upper line (dots) represents the sum of the lower modes (i.e., sum of mode 1 until mode (i) and the lower line (stars) represents the sum of the higher modes (i.e., sum of mode i until mode 130). The circle (b) represents the sum of higher modes at which the force is optimally predicted. The squares (a, c) represent two sums of modes having the same RMSD chosen for further illustration. (B) Normalized force and normalized EMG amplitudes for three different sum of higher modes. Condition a represents the sum of all modes (equivalent to the raw monopolar signals), condition b uses the sum of mode 6 until mode 130 and the condition c the sum of mode 45 until mode 130. (C) The fluctuations of the force and the EMG signal over the plateau region. Note that condition b matches the force pattern most properly (B,b) and also shows highest correlations over the plateau-region (C,b).

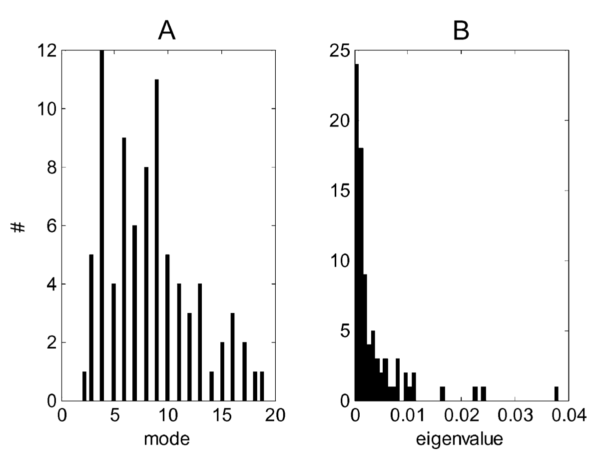

Fig. 6. Distributions of the optimal sum of the higher modes for force estimation quality (RMSD). (A) The histogram for the optimal sum of higher modes indicated with the starting mode. (B) The histogram of the eigenvalue threshold of the optimal sum of higher modes.

(MON, PCA, OMB, LAP, and CBI), respectively [Fig. 7(C)]. An ANOVA after application of a Fisher z transform, revealed a significant effect of EMG procedures $(p < 0.01)$. Similarly, median correlation coefficients over the plateau region were 0.28 (range: -0.15:0.70), 0.52 (0.10:0.96), 0.38 (-0.09:0.89), 0.47 (-0.11:0.89) and 0.31(-0.30:0.85), respectively [Fig. 7(D)], showing a significant effect of procedures $(p < 0.01)$.

IV. Discussion

This study shows that the accuracy of force predictions based on data obtained with high-density EMG grids depends on which EMG procedures are applied. We have shown the practically relevant effect of different directions of bipolar electrode configuration. We further demonstrated that PCA can be used as a promising alternative to spatial filter manipulations.

A. Bipolar Configuration Direction

The analysis of different bipolar electrode-pair directions (Fig. 2) showed a difference of about 13% between the worst and the best force estimation quality (directions 4 and 3, respectively). These two extremes were found for two orthogonal bipolar electrode directions. The other two directions showed intermediate results. We realize that the interelectrode distances are not equal between the directions studied. However, a previous study showed that small changes of interelectrode distances did not affect force estimation quality [4]. In addition, unpublished dissection studies showed superficial muscle fibers of triceps brachii as being mostly in line with bipolar electrode direction 3 in Fig. 2. We conclude with other studies and recommendations [5], [17] that bipolar configurations should be along the expected main fiber direction of the muscle. We found that all EMG amplitudes followed the contraction pattern. The "aligned" configuration 3) not only had the lowest SNR over the plateau-region, resulting in the lowest RMSD, it also was least sensitive to elbow angle. Thus, alignment of the electrodes with the expected muscle fibers appears to be beneficial for two reasons, both contributing to the robustness or fidelity of EMG-based force estimation.

B. Principal Component Analysis

About 90% of the power in the monopolar EMG signals [Fig. 1(B)] could be represented by a single mode [Fig. 3]. The eigenvector of this mode showed a fairly homogeneous "carpet"-shape [Fig. 4, eigenvector of mode 1], having peak values at the upper left corner of the EMG grid. Accordingly, the monopolar EMG signals were highly correlated, which occurs because monopolar EMG consists to large extent of so-called far-field activity [18], possibly even from motor units of (distant) other muscles. In terms of force prediction, the first mode showed a substantially higher RMSD compared to the monopolar signal itself [Fig. 5(A)]. Thus, this first mode does not contribute to an improvement in force estimation quality. In contrast, subtracting the first few modes improved both the RMSD over the entire pattern and the correlation over the plateau region. This approach may work in a similar way to spatial differentiation (e.g., CBI), which also removes common information. In eliminating the first five modes, as mentioned above, the summed eigenvalues imply that about

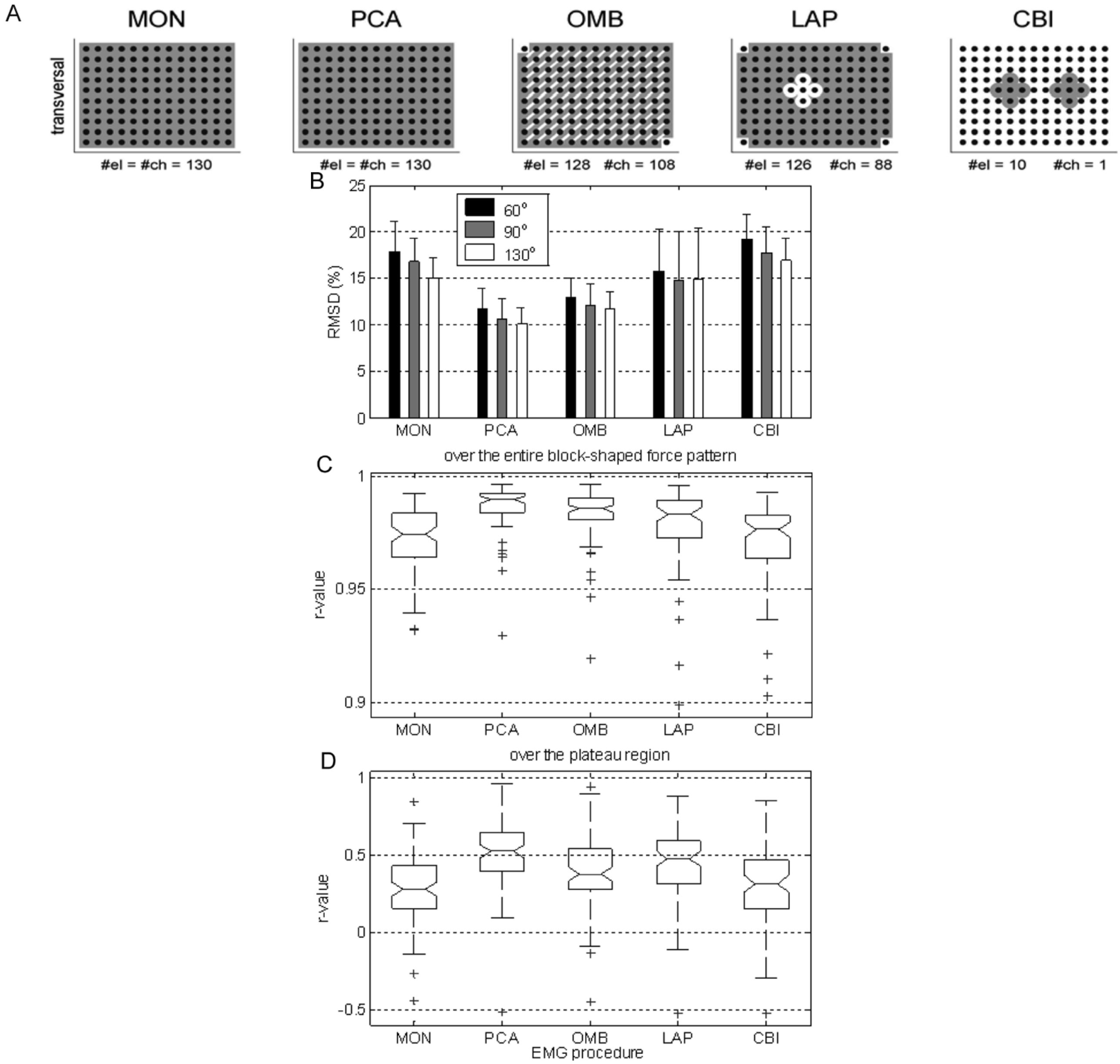

Fig. 7. (A) Results of five different EMG procedures: monopolar basic set (MON), PCA (eigenvalue threshold), optimally aligned multiple bipolar direction (OMB), Laplacian configuration (LAP) and conventional bipolar configuration (CBI). Black dots represent electrodes, dark surface shows the section of the 13 × 10 electrode grid used and white colors the nature of the electrode configuration. The label "el" indicates the amount of electrodes used and the label "ch" indicates the amount of channels used for the specific configuration. Note, that the first two conditions (MON and PCA) are geometrically unconstrained with respect to the underlying muscle fibers. (B) RMSD for the five procedures. Bars represent average values over subjects for different elbow angles and error bars represent their standard deviation. (C), (D) Correlation coefficients between force and EMG signals for the five procedures over the entire force pattern (C) and over the plateau region (D). The middle line represents the median value, error bars represents the range. The lower and higher boxes, with notches, represent the interquartile range and plus-signs represent outliners. The Y-axis scaling was adapted to illustrate the effect on the correlation coefficients.

99% of the collected monopolar signal power is dispensable for force estimation. Interestingly, a study looking for the optimal high-pass cutoff frequency showed optimal EMG-based force estimation when using cut-off frequencies that also removed about 99% of the original EMG signal power [19].

A physiological interpretation of the different modes remains a challenge. However, at least the modes at both ends of the spectrum appear to have an interpretable structure. Mode 1 may be interpreted as common background or weighted mean of the original monopolar EMG determined by far field potentials [18]. Recall that this mode accounted for about 90% [Fig. 3, mode 1] of the variance in the monopolar data. Due to the (mirror) eigenvector-symmetries in the subsequent modes (e.g., Fig. 4, mode 2 and 6) one may speculate that they depict the direction of propagation of EMG activity (traveling waves). For instance, the combination of mode 2 and 6 may suggest an oblique propagation direction in accordance with the expected muscle fiber arrangement. A more detailed analysis, however, is beyond the scope of the present article. At the other end of the spectrum, the lack of amplitude modulation of the projections of the highest modes with force suggests that these modes represent noise. Recall that the highest modes (e.g., Fig. 4, mode 130) capture little of the data's variance, i.e., they have very small power (eigenvalues $\sim 10-7$).

C. EMG Procedures

CBI resulted in the highest RMSD (Fig. 7), which may be due the fact that it was not aligned with respect to the underlying muscle fiber direction. In addition, a previous study [4] showed that the collection surface affects force estimation quality and obviously with respect to this factor CBI differs from all other procedures, which used the full grid. MON resulted in a lower force estimation quality than OMB and LAP. This is in line with the low predictive value of the lower modes in the PCA. Although LAP configurations are less constrained with respect to the underlying muscle fiber arrangement than bipolar configurations, LAP did not improve force estimation compared to the OMB. Reasons for this finding may be the reduction of the collection depth with higher order filtering configurations [20], [21] or still a misalignment of the configuration direction with respect to the muscle fiber arrangement. The lowest RMSD was obtained with PCA, improving force estimation by about 35% compared to MON, about 40% compared to CBI and about 12% compared to OMB. Interestingly, the PCA, being independent of the underlying muscle fiber direction, showed the same sensitivity to elbow angle as OMB. Thus, the PCA was not able to negate the effect of elbow angle on force prediction quality. This systematic effect of elbow angle is probably due to the rigid EMG grid covereing a larger fraction of the muscle at shorter muscle length, as a result of the pennate architecture of the triceps brachii muscle.

The correlation between force and EMG over the entire contraction pattern mainly mirrored the results of the RMSD analysis, except that MON resulted in the lowest correlations [Fig. 7(B), (C)]. As expected, the correlation between force and EMG over the plateau region showed much lower values than over the entire force pattern [Fig. 7(D)]. But also for this analysis the PCA showed the highest correlations, being the only procedure having exclusively positive correlation coefficients.

PCA can be compared to other methods (e.g., whitening or high-pass filtering) which affect the temporal characteristics of the EMG signal. For example, whitening is known to temporally de-correlate the EMG signal and to result in a reduction of the SNR [22]. Also filtering at increasing high-pass cutoff frequencies has been shown to improve muscle force estimation [19]. PCA transforms the original data into linearly independent vectors (see [13] for a review). Thus, when applying PCA on a high-density EMG grid, the signals can be interpreted as spatially de-correlated. Both approaches appear to be beneficial in EMG-based muscle force prediction. Although a combination of multiple channel EMG and whitening has been used with positive results on force estimation quality [23], a combination of PCA and temporal de-correlation has to our knowledge not yet been used.

D. Limitation and Outlook

In the present study the triceps brachii muscle was chosen for the following reasons. This muscle is larger than the size of the EMG grid; thus, crosstalk from neighboring muscles was minimal. Anatomically, this muscle has no relevant synergists; thus, a direct comparison between EMG and moment can be performed. The antagonists (e.g., biceps brachii muscle) were assumed to interfere minimally with the external moment, but may have affected the small force fluctuations over the plateau region [Fig. 5(C)].

The precise location of the electrodes with respect to the anatomy of the covered muscle fibers (i.e., neuro-muscular junctions and the fiber-tendon termination), was not considered here. Thus, the spatial propagation of the motor unit action potentials was not explicitly analyzed.

The isometric rectangular contraction pattern was deemed appropriate for a comparison of the EMG procedures in estimating muscle force. Since this pattern has steep and narrow ascending and descending limbs, it is not sensitive to the overall EMG force relation (e.g., nonlinearity between EMG and force).

Applying PCA as an extraction method in force prediction from multiple channels of bipolar or higher-order configurations (such as OMB, LAP in the present study), although feasible, would re-introduce an undesirable bias due to the possible misalignment with the actual muscle fiber direction.

In considering the EMG signals as a multivariate data set, PCA was a first unbiased choice allowing for algebraic computation and comparison to other, more conventional electrode configurations. Future work will address alternative methods (e.g., independent component analysis, K-mean clustering) that might further improve the quality of the muscle force estimation and extent this to dynamic contractions.

V. Conclusion

High-density EMG is a powerful tool for the prediction of force output of a muscle but the result depends on the way in which the EMG signal is recorded and also on the principles and parameters of the signal processing. For instance, the alignment of bipolar electrode pairs affects the force estimation quality. In the present study, the lowest RSMD was obtained with the electrode direction aligned with the expected superficial muscle fiber direction, being 13% lower than in the worst performing (orthogonal) electrode direction. PCA can be used as an alternative to electrode configurations and improved force estimation quality by about 40% compared to CBI and about 12% compared to OMB. Apparently, any order of spatially filtering electrode configurations suffers from a biased choice of the configuration direction. PCA appears to be a valuable tool for extracting relevant force-related information from a high-density EMG grid and therewith improving the quality of muscle force estimation.

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